

STANFORD ARTIFICIAL INTELLIGENCE PROJECT  
MEMO AIM-137

COMPUTER SCIENCE DEPARTMENT  
REPORT NO. CS-186

AD715513

AN EMPIRICAL STUDY OF FORTRAN PROGRAMS

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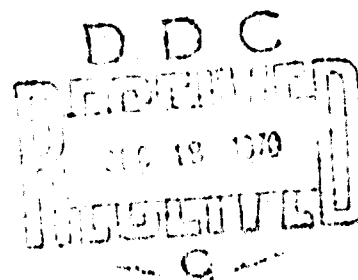
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## An Empirical Study of FORTRAN Programs

Donald E. Knuth

**Abstract:** A sample of programs, written in FORTRAN by a wide variety of people for a wide variety of applications, was chosen "at random" in an attempt to discover quantitatively "what programmers really do." Statistical results of this survey are presented here, together with some of their apparent implications for future work in compiler design. The principal conclusion which may be drawn is the importance of a program "profile," namely a table of frequency counts which record how often each statement is performed in a typical run; there are strong indications that profile-keeping should become a standard practice in all computer systems, for casual users as well as system programmers. This paper is the report of a three month study undertaken by the author and about a dozen students and representatives of the software industry during the summer 1970. It is hoped that a reader who studies this report will obtain a fairly clear conception of how FORTRAN is being used, and what compilers can do about it.

This research was supported, in part, by IBM Corporation, by Xerox Corporation, and by the Advanced Research Projects Agency of the Office of the Department of Defense (SD-183).

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# An Empirical Study of FORTRAN Programs

Ronald E. Knuth

## 1. Introduction

Designers of compilers and instructors of computer science usually have comparatively little information about the way in which programming languages are actually used by typical programmers. We think we know what programmers generally do, but our notions are rarely based on a representative sample of the programs which are actually being run on computers. Since compiler writers must prepare a system capable of translating a language in all its generality, it is easy to fall into the trap of assuming that complicated constructions are the norm when in fact they are infrequently used. There has been a long history of optimizing the wrong things, using elaborate mechanisms to produce beautiful code in cases that hardly ever arise in practice, while doing nothing about certain frequently occurring situations. For example, the present author once found great significance in the fact that a certain complicated method was able to translate the statement

$$C[IXN+J] := ((A+X) \times Y) + 2.768 + ((L-M) \times (-K)) / Z$$

into only 19 machine instructions compared to the 21 instructions obtained by a previously published method due to Galler et al. (See Knuth [11].) The fact that arithmetic expressions usually have an average length of only two operands, in practice, would have been a great shock to the author at that time!

There has been widespread realization that more data about language use is needed; we can't really compare two different compiler algorithms

until we understand the input data they deal with. Of course, the great difficulty is that there is no such thing as a "typical programmer"; there is a tremendous variation among programs written by different people with different backgrounds and sympathies, and indeed there is considerable variation even in different programs written by the same person. Therefore we cannot trust any measurements to be very accurate, although we can measure the degree of variation in an attempt to determine how significant it is. Not all properties of programs can be reduced to simple statistics; it is necessary to study selected programs in detail in order to appreciate their characteristics more clearly. For a survey of early work on performance measurement and evaluation, see Calingaert [2] and Cerf [3].

During the summer of 1970, the author worked together with several other people, in order to explore the nature of actual programs and the corresponding implications both for software design and for computer science education. Members of the group included G. Autrey, D. Brown, I. Fang, D. Ingalls, J. Low, F. Maginnis, M. Maybury, D. McNabb, E. Satterthwaite, R. Sites, R. Sweet, and J. Walters; these people did all of the hard work which led to the results in this report. Our results are by no means a definitive analysis of programming behavior; our goal was to explore the various possibilities, as a group, in order to set the stage for subsequent individual research, rather than to go off in all directions at once. Each week the entire group had an eight-hour meeting, in order to discuss what had been learned during the previous week, hoping that by combining our differing points of view we might arrive at something reasonably close to Truth.

A first idea for obtaining "typical" programs was to go to Stanford's Computation Center and rummage in the wastebaskets and the recycling bins.

This gave results but showed immediately what should have been obvious: wastebaskets usually receive undiagnosed programs. Furthermore, it seems likely that compilers usually are confronted with undiagnosed programs, too; so it was necessary for us to choose whether we wanted to study the distributions of syntax errors, etc., or to concentrate on working programs. Some excellent analyses of common errors have already been made (Freeman [4]; Moulton and Miller [12]), and one of our main goals was to study the effects of various types of optimization; so we decided to restrict ourselves to programs which actually ran to completion.

The wastebasket method turned up some interesting programs, but it was not really satisfactory. If we wanted to automate the process, extensive typing from the listings would have been necessary; so we tried another tack. Our next method of obtaining programs was to post a man by the card reader at various times; he would ask for permission to copy decks onto a special file. Fifteen programs, totalling about 5000 cards, were obtained in this way; but the job was very time-consuming since it was necessary to explain the objectives of our project each time and to ask embarrassing questions about the status of people's programs.

The next approach was to probe randomly among the semi-protected files stored on disks, looking for source text; this was successful, resulting in 33 programs, totalling about 20,000 cards. We added nine programs from the CSD subroutine library and three programs from the "Scientific Subroutine Package", and some production programs from the Stanford Linear Accelerator Center. A few classical benchmark programs (nuclear codes, weather codes, and aerospace calculations) were also contributed by IBM representatives, and to top things off we threw in some programs of personal interest to members of the group.

Our procedure gave us a quite varied collection of programs: some large, some small; some sophisticated, some crude; some important, some trivial; some for production, some for play; some numerical, some combinatorial.

It is well-known that different programming languages evolve different styles of programming, so our study was necessarily language-dependent. For example, one would expect that expressions in APL programs tend to be longer than in FORTRAN programs. But virtually all of the programs obtained by our sampling procedure were written in FORTRAN (this was the first surprise of the summer), so our main efforts were directed toward the study of FORTRAN programs.✓

Was this sample representative? Perhaps the users of Stanford's computers are more sophisticated than the general programmers to be found elsewhere; after all we have such a splendid Computer Science Department! But it is doubtful whether our Department had any effect on these programs, because for one thing we don't teach FORTRAN; it was distressing to see what little impact our courses seem to be having, since virtually all of the programs we saw were apparently written by people who had learned programming elsewhere. Furthermore, the general style of programming that we found showed very little evidence of "sophistication"; if it was better than average, the average is too horrible to contemplate! (This remark is not intended as an insult to Stanford's programmers; after all we were invading their privacy, and they would probably have written the programs differently

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\*/ By contacting known users of ALGOL, it was possible to collect a fairly representative sample of ALGOL W programs as well. The analysis of these programs is still incomplete; preliminary indications are that the increased flexibility of data types in ALGOL W makes for much more variety in the nature of inner loops than was observed in FORTRAN, and that the improved control structures make GO TO's and labels considerably less frequent. A comprehensive analysis of ALGOL 60 programs has recently been completed by B. Wichmann [19].

We analyzed one PL/I program by hand. COBOL is not used at Stanford's Computation Center, and we have no idea what typical COBOL programs are like.

if they had known the code was to be scrutinized by self-appointed experts like ourselves. Our purposes were purely scientific, in an attempt to find out how things are, without moralizing or judging people's competence. The point is that the Stanford sample seems to be reasonably typical of what might be found elsewhere.) Another reason for believing that our sample was reasonably good is that the programs varied from text-editing and discrete calculations to number-crunching; they were by no means from a homogeneous class of applications. On the other hand we do have some definite evidence of differences between the Stanford sample and another sample of over 400 programs written at Lockheed (see Section 2 of this report).

The programs obtained by this sampling procedure were analyzed in various ways. First we performed a static analysis, simply counting the number of occurrences of easily recognizable syntactic constructions. Statistics of this kind are relevant to the speed of compilation. The results of this static analysis are presented in Section 2. Secondly, we selected about 25 of the programs at random and subjected them to a dynamic analysis, taking into account the frequency with which each construction actually occurs during one run of the program; statistics of this kind are presented in Section 3. We also considered the "inner loops" of 17 programs, translating them by hand into machine language using various styles of optimization in an attempt to weigh the utility of various local and global optimization strategies; results of this study are presented in Section 4. Section 5 of this paper summarizes the principal conclusions we reached, and lists several areas which appear to be promising for future study.

### Static Statistics

We examined a large number of FORTRAN programs to see how frequently certain constructions are used in practice. Over 250,000 cards (representing 440 programs) were analyzed by Mr. Maybury at the computer center of Lockheed Missiles and Space Corporation in Sunnyvale.

Table 1 shows the distribution of statement types. A "typical Lockheed program" consists of 120 comment cards, plus 178 assignment statements, 11.5 IF's, 50 GO TO's, 34 CALL's, 21 CONTINUE's, 18 WRITE's, 13 FORMAT's, 17 DO's, 70 miscellaneous other statements, and 31 continuation cards (mostly involving COMMON or DATA). Essentially the same overall distribution of statement types was obtained when individual groups of about 50 programs were tested, so these statistics tended to be rather stable. We forgot to test how many statements had nonblank labels.

The same test was run on a much smaller but still rather large collection of programs from our "Stanford sample" (about 11,000 cards). Unfortunately the corresponding percentages shown in Table 1 do not agree very well with the Lockheed sample; Stanfordites definitely use more assignments and less IF's and GO's than Lockheedians. A superficial examination of the programs suggests that Lockheed programmers are perhaps more careful to check for erroneous conditions in their data. Note also that 2.7 times as many comments appear on the Lockheed programs, indicating somewhat more regimentation. The professional programmers at Lockheed have a distinctly different style from Stanford's casual coders.



Table 1. Distribution of statement types.

	Lockheed		Stanford	
	Number	Percent *	Number	Percent *
Assignment	78455	41	4869	51
IF	27917 **	14.5 **	816 **	8.5 **
GOTO	24042	13	777	8
CALL	15125	8	339	4
CONTINUE	9145	5	309	3
WRITE	7795	4	508	5
FORMAT	7635	4	380	4
DO	7476	4	457	5
DATA	4468	2	28	.3
RETURN	3639	2	186	2
DIMENSION	3492	2	141	1.5
COMMON	2908	1.5	263	3
END	2565	1	121	1
BUFFER	2501	1	0	0
SUBROUTINE	2001	1	93	1
REWIND	1724	1	6	-
EQUIVALENCE	1382	.7	113	1
ENDFILE	765	.4	2	-
INTEGER	657	.3	34	.3
READ	586	.3	92	1
ENCODE	583	.3	0	-
DECODE	557	.3	0	-
PRINT	345	.2	5	-
ENTRY	279	.1	15	.2
STOP	190	.1	11	.1
LOGICAL	170	.1	9	.1
REAL	147	.1	3	-
IDENT	106	.1	0	-
DOUBLE	3	-	29	1
OVERLAY	82	-	0	-
PAUSE	57	-	6	.1
ASSIGN	57	-	4	-
PUNCH	52	-	5	.1
EXTERNAL	23	-	1	-
IMPLICIT	0	-	16	1.5
COMPLEX	6	-	0	-
NAMelist	5	-	0	-
BLOCKDATA	1	-	2	-
INPUT	0	-	0	-
OUTPUT	0	-	0	-
COMMENT	52924	(28)	1090	(11)
CONTINUATION	13709	(7)	636	(7)

\* Percent of total number of statements excluding comments and continuation cards.

\*\* The construction 'IF ( ) statement' counts as an IF as well as a statement, so the total is more than 100%.

The DO loops were further investigated to determine their length and depth of nesting: about 99% of the DO statements used the default increment of 1. Most DO loops were quite short, involving only one or two statements:

length	1	2	3	4	5	> 5
Number	506	1407	758	576	1043	1043
Percent	50	18.5	9.5	7	13	13

The depth of DO nesting was subject to considerable variation; the following totals were obtained:

Depth	1	2	3	4	5	> 5
Number	4211	1853	1194	437	118	120
Percent	55.5	23	15	5.5	1.5	1.5

Of the 28783 IF statements scanned, 8858 (30%) were of the "old style" IF (...)  $n_1, n_2, n_3$  or IF (...)  $n_1, n_2$  while the other 19925 (70%) had the form IF (...) statement; 14258 (71%) of the latter were "IF (...) GO TO". (These count also as GO TO statements.) Only 1107 of the 25719 GO TO statements were computed (switch) GO's.

An average of about 48 trailing blank columns was found per non-comment card. A compiler's lexical scanner should therefore include a high-speed skip over blanks.

Assignment statements were analyzed in some detail. There were 83304 assignment statements in all; and 56751 (68%) of them were trivial replacements of the form  $A = B$  where no arithmetic operations are present!\*/ The remaining assignments included 10418 of the form  $A = A \text{ op } \alpha$ , i.e., the first operand on the right is the same as the variable on the left. An

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\*/ In the Stanford sample the corresponding figures were 2379 out of 4869 (49%); this was another example of a Lockheed-vs.-Stanford discrepancy.

attempt was made to rate the complexity of an assignment statement, counting one point for each + or - sign, five for each \*, and 3 for each /; the distribution was

Complexity	0	1	2	3	4	5	6	7	8	9
Number	50751	14045	1124	106	267	2436	1988	562	2359	552
Percent	68	17.5	1.3	.1	.3	3	2	.6	3	.6

Occurrences of operators and constants were also tallied:

Operator	+	-	*	/	**	=	standard function	constant
Occurrences	17973	10298	12348	4739	1108	90257	3994	49386

It is rather surprising to note that 7200 (40%) of the additions had the form  $\alpha+1$ ; 349 (3%) of the multiplications had the form  $\alpha*2$ ; 180 (4%) of the divisions had the form  $\alpha/2$ ; 427 (39%) of the exponentiations had the form  $\alpha**2$ . (We forgot to count the fairly common occurrences of  $2*\alpha$ ,  $2.*\alpha$ ,  $\alpha*2.$ ,  $\alpha/2.$ ,  $2.0*\alpha$ , etc.)

The program analyzed indices, although it was unable to distinguish subscripted variables from calls on programmer-defined functions. Of the 166,599 appearances of variables, 97051 (58%) were unindexed, 50979 (30.5%) had one index, 16181 (9.5%) had two, 2008 (1%) had three, and 380 (.2%) had four.

Another type of "static" test on the nature of FORTRAN programs was also made, in an attempt to discover the complexity of control flow in the programs. John Cocke's "interval reduction" scheme (see [4]) was applied to fifty randomly-selected FORTRAN programs and subroutines, and in every case the flow graph was reduced to a single vertex after six or less transformations. The average number of transformations required per program was only 2.75.

The obvious conclusion to draw from all these figures is that compilers spend most of their time doing surprisingly simple things.

### Dynamic Statistics

The static counts tabulated above are relevant to the speed of compilation, but they do not really have a strong connection with the speed of object program execution. We need to give more weight to statements that are executed more frequently.

Two different approaches to dynamic program analysis were explored in the course of our study, the method of frequency counts or program profiles and the method of program status sampling. The former method inserts counters at appropriate places of the program in order to determine the number of times each statement was actually performed; the latter method makes use of an independent system program which interrupts the object program periodically and notes where it is currently executing instructions.

Frequency counts were commonly studied in the early days of computers (see von Neumann and Goldstine [14]), and they are now experiencing a long-overdue revival. We made use of a program called FORDAP, which had been previously developed in connection with some research on compilation; FORDAP takes a FORTRAN program as input, and outputs an equivalent program which also maintains frequency counts and writes them onto a file. When the latter program is compiled and run, its output will include a listing of the executable statements together with their frequency counts. See Figure 1, which illustrates the output corresponding to a short program, using an extension of FORDAP which includes a rough estimate of the relative cost of each statement (Ingalls [9]). The principles of preparing such a routine were independently developed at UCLA by S. Crocker and E. Russell [15]; Russell's efforts were primarily directed towards a study of potential parallelism in programs, but he also included some serial analyses of large scale routines which exhibit the same phenomena observed in our own studies.

Frequency counts add an important new dimension to the FORTRAN programs; indeed, it is difficult to express in words just how tremendously "eye-opening" they are! Even the small example in Figure 1 has a surprise (the frequency counts reveal that about half the running time is spent in the subroutine linkage of the FUN function). After studying dozens of FORDAPed programs, and after experiencing the reactions of programmers who see the frequency counts of their own programs, our group came to the almost unanimous conclusion that all software systems should provide frequency counts to all programmers, unless specifically told not to do so!

The advantages of frequency counts in debugging have been exploited by E. Satterthwaite [16] in his extensions to Stanford's ALGOL W compiler. They can be used to govern selective tracing and to locate untested portions of a program. Once the program has been debugged, its frequency counts show where the "bottlenecks" are, and this information often suggests improvements to the algorithm and/or data structures. For example, we applied FORDAP to itself, since it was written in FORTRAN, and we immediately found that it was spending about half of its time in two loops that could be greatly simplified; this made it possible to double the speed of FORDAP, in less than an hour's work, without even looking at the rest of the program. (See Example 2 in Section 4 below.) The same thing happened many times with other programs.

Thus our experience has suggested that frequency counts are so important they deserve a special name; let us call the collection of frequency counts the profile of a program.

Programs typically have a very jagged profile, with a few sharp peaks. As a very rough approximation, it appears that the n-th most important statement of a program from the standpoint of execution time accounts for

EXECUTABLE STATEMENTS		EXECUTIONS	COST
10	READ (5,1) XU,YU,H,JNT,IENT	2	100
	IF (IENT) 20,40,20	2	4
20	WRITE (6,2) H,XU,YC	1	50
	CALL RN2 (FUN,H,XU,YU,JNT,IENT,A)	1	2
	STEP=FLCAT(JNT)*H	1	11
	X=XU	1	1
	LO 30 I=1,IENT	1	1
	X=X+STEP	1	2
30	WRITE (6,3) X,A(I)	30	60
	GO TO 10	30	1530
40	STOP	1	1
	END	1	1
FUNCTION FUN(X,Y)		1200	18000
FUN =1./X		1200	9600
FRETURN		1200	6000
END			
SUBROUTINE RK2(FUN,H,XI,YI,K,N,VEC)		1	15
H2=H/2.		1	8
Y=YI		1	1
X=XI		1	1
DO 2 I=1,N		1	2
DU 1 J=1,K		1	60
T1=H*FUN(X,Y)		30	2700
T2=H*FUN(X+H2,Y+T1/2.)		300	5400
T3=H*FUN(X+H2,Y+T2/2.)		300	5400
T4=H*FUN(X+H,Y+T3)		300	3300
Y= Y+(T1+2.*T2+2.*T3+T4)/6.		300	6900
1 X=X+H		300	900
2 VEC(I)=Y		30	90
RETURN		1	5
END			

Figure 1. The profile of a short program.

about  $(\alpha-1)\alpha^{-n}$  of the running time, for some  $\alpha$  and for small  $n$ . We also found that less than 4% of a program generally accounts for more than half of its running time. This has important consequences, since it means that programmers can make substantial improvements in their own routines by being careful in just a few places; and optimizing compilers can be made to run much faster since they need not study the whole program with the same amount of concentration.

Table 2 shows how the relative frequency of statement types changes when the counts are dynamic instead of static; this table was compiled from the results of 24 FORDAP runs, with the statistics for each program weighted equally. We did not have time to break down these statistics further (to discover, for example, the distribution of operators, etc.), except in one respect: 45% of the assignment statements were simply replacements (of the form  $A = B$  where  $B$  is a simple variable or constant), when counting statically, but this dropped to 35% when counting dynamically. In other words, replacements tend to occur more often outside of loops (in initialization sections, etc.).

Table 2. Distribution of executable statements.

	Static	(percent)	Dynamic
Assignment	51		67
IF	10		11
GO TO	9		9
DO	9		3
CALL	5		3
WRITE	5		1
CONTINUE	4		7
RETURN	4		3
READ	2		0
STOP	1		0

The other approach to dynamic statistics-gathering, based on program status sampling, tends to be less precise but more realistic, in the sense that it shows how much time is actually spent in system subroutines. We used and extended a routine called PROGTIME [10] which was originally developed by T. Y. Johnston and R. H. Johnson to run on System 360 under MVT. PROGTIME spawns the user program as a subtask, then samples its status word at regular intervals, rejecting the datum if the program was dormant since its last interruption. An example of the resulting "histogram" output appears in Figure 2; it is possible (although not especially convenient) to relate this to the FORTRAN source text.

In general, the results obtained from PROGTIME runs were essentially what we would have expected from the FORDAP produced profiles, except for the influence of input/output editing times. The results of FORDAP would have led us to believe that the code between relative locations 015928 and 015A28 in Figure 2 would consume most of the running time, but in fact 70% of the time was spent in those beloved system subroutines IHCECOMH and IHCFCVTH (relative locations 016A88 through 019080 ). Roughly half of the programs we studied involved substantial amounts of input/output editing time, and this led us to believe that considerable gains in efficiency would be achieved if the compilers would do the editing in-line wherever possible. It was easy to match up the formats with the quantities to be edited, in every case we looked at. However, we did not have time to study the problem further to investigate just how much of an improvement in performance could be expected from in-line editing. Clearly the general problem of editing deserves further attention, since it seems to use up more than 25% of the running time of FORTRAN programs in spite of the extremely infrequent occurrence of actual input/output statements reflected in Table 2.





Due to the random nature of the sampling process, two PROGTIMES of the same program will not give identical results. It is possible to get accurate frequency counts and accurate running times by using the technique of "jump tracing" (see Gaines [7, Chapter 3]). A jump trace routine scans a program down to the next branch instruction, and executes the intervening code at machine speed; when a branch occurs the location transferred to is written onto a file. Subsequent processing of the file makes it possible to infer the frequency counts. The jump trace approach does not require auxiliary memory for counters, and it can be used with arbitrary machine language programs. Unfortunately we did not have time to develop such a routine for Stanford's computers during the limited time in which our study was performed.

#### 4. The Inner Loops

We selected 17 programs at random for closer scrutiny; this section contains a summary of the main features of these programs. (It is worth emphasizing that we did not modify the programs nor did we discard programs that did not produce results in accordance with our preconceived ideas; we analyzed every routine we met whether we liked it or not! The result is hopefully a good indication of typical FORTRAN programming practice, and we believe that a reader who scans these programs will obtain a fairly clear conception of how FORTRAN is being used.) First the program profile was found, by running it with FORDAP and PROGTIME. (This caused the chief limitation on our selection, for we were unable to study programs for which input data was on inaccessible tapes or otherwise unavailable.) In each case a glance at the profile reduced the program to a comparatively

small piece of code which represented the majority of the execution time exclusive of input/output statements. These "inner loops" of the programs are presented here; the names of identifiers have been changed in order to give some anonymity, but no other changes have been made.

In each case we hand-translated the inner loop into System/360 machine language, using five different styles of "optimization":

Level 0. Straight code generation according to classical one-pass compilation techniques.

Level 1. Like level 0 but using local optimizations based on a good knowledge of the machine; common subexpressions were eliminated and register contents were remembered across statements if no labels intervene, etc., and the index of a DO was kept in a register, but no optimizations requiring global flow analysis were made.

Level 2. "Machine-independent" optimizations based on global flow analysis, including constant folding, invariant expression removal, strength reduction, test replacement, and load-store motion (cf. Allen [1]).

Level 3. Like level 2 plus machine-dependent optimizations based on the 360, such as the use of BXLE, LA, and the possibilities afforded by double indexing.

Level 4. The "best conceivable" code that would be discovered by any compiler imaginable. Anything goes here except a change in the algorithm or its data structures.

These styles of optimization are not extremely well defined, but in each case we produced the finest code we could think of consistent with that

level. (In nearly every case this was noticeably better than the optimizations produced by the existing FORTRAN compilers; FORTRAN H OPT 02 would presumably be able to reach level 3 if it were carefully tuned.) Level 4 represents the ultimate achievable, by comparison with what is realized by current techniques, in an attempt to assess whether or not an additional effort would be worthwhile.

These styles of optimization can best be appreciated by studying Example 1 for which our machine language coding appears in the Appendix to this paper. It is appropriate to restrict our attention solely to the inner loop, since the profiles show that the effect of optimization on this small part of the code is very indicative of the total effect of optimization on the program as a whole.

In order to compare one strategy to another, we decided to estimate the quality of each program by hand instead of actually running them with a timer as in [18]. We weighted the instructions in a crude but not atypical manner as follows: Each instruction costs one unit, plus one if it fetches or stores an operand from memory or if it is a branch that is taken, plus a penalty for specific slower opcodes:

Floating add/subtract,	add 1
Multiply,	add 5
Divide,	add 8
Multiply double,	add 13
Shift,	add 1
Load multiple,	add $\frac{1}{2} n$ (n registers loaded)
Store multiple,	add $\frac{1}{3} n$ (n registers stored)

This evaluation corresponds roughly to 1 unit per 0.7 microseconds on our model 67 computer. Other machine organizations ("pipelining", etc.) would, of course, behave somewhat differently, but the above weights should give some insight. We also assumed the following additional costs

for the time spent in library subroutines (cf. [8]):

SQRT	85
SIN, COS	110
ALOG	120
ERF	130
Complex multiply	150
Real ** Integer	75

Example 1. The first program we studied involved 140 executable statements, but the following five represented nearly half of the running time:

```
DO 2 J = 1,N
T = ABS(A(I,J))
IF (T-S) 2,2,1
1 S = T
2 CONTINUE
```

Statement 1 was executed about half as often as the others in the loop.

The programs in the Appendix have a "score" of

37.5 , 28.5 , 14 , 8 , 7

for levels 0, 1, 2, 3, 4 respectively.

The same program also included another time-consuming loop,

```
DO 3 J = 1,N
3 A(I,J) = A(I,J)*B
```

for which the respective scores are

51 , 29 , 17 , 12 , 11 .

In this case level 0 is penalized for calculating the subscript twice.

Example 2. (This came from the original FORDAP program itself.) Although there were 455 executable statements, over half of the program time was spent executing two loops like this:

```
DO 1 J = 38,53
IF (K(I).EQ.L(J)) GO TO 3
1 CONTINUE
2 ....
```

the five styles of translation give respective scores of

1.0, 1.0, 1.0, 1.0, 1.5.

Level 4's score of 1.5 is obtained in an interesting way which applies to several other loops we had examined earlier in the summer; we call it the technique of combining tests. The array element L(54) is set equal to K(1), so that the loop involves only one test; then after reaching L3, if J = 54 we go back to L2. The code is

```
Q1  LA 5,8(0,3)
    C 4,0(0,3)
    BER 5          (Register 5 contains A(I3))
    C 4,4(0,3)
    BNE Q1
L5  ...
```

If necessary, L(54) could be restored.

Of course, in this particular case the loop is executed only 16 times, and so it could be completely unrolled into 32 instructions

```
C 4,L(28)
BER 5
C 4,L(39)
BER 5
:
:
C 4,L(53)
BER 5
```

reducing the "score" to 3. But in actual fact the L table was loaded in a DATA statement, and it contained a list of special character codes; a more appropriate program would replace the entire DO loop by a single test

```
IF (LT(K(I))) 1,3,1
```

for a suitable table LT, thereby saving over half the execution time of the program. (Furthermore, the environment of the above DO loop was

```
DO 2 I = 7,72
```

so that any assembly language programmer would have reduced the whole business to a single "translate and test".)

Example 3.

```
DOUBLE A,B,D
DO 1 K = 1,N
  A = T(I-K,1+K)
  B = T(I-K,J+K)
1 D = D-A*B
```

(This is one of the few times we observed double precision being used, although the numerical analysis professors in our department strongly recommend against the short precision operators of the 360; it serves as another indication that our department seems to have little impact on the users of our computer!) The scores for this loop are

89 , 67 , 38 , 13 , 12 ;

here level 2 suffers from some clumsiness in the indexing and a lack of knowledge that an ME instruction could be used instead of MD.

Example 4. Here the inner loop is longer and involves a subroutine call. The following code accounted for 70% of the running time; the entire program had 214 executable statements.

```
DO 1 K = M,20
  CALL RAND(R)
  IF (R .GT. .81) N(K) = 1
1 CONTINUE
...
SUBROUTINE RAND(R)
  J = I*65539
  IF (J) 1,2,2
1 J = J+2147483647+1
2 R = J
  R = R*.4656613E-9
  I = J
  K = K+1
  RETURN
END
```

(Here we have a notoriously bad random number generator, which the programmer must have gotten out of an obsolete reference book; it is another example of our failure to educate the community.) Conversion from integer to real is assumed to be done by the sequence

A = 1.0  
 B = 1.0  
 C = 1.0  
 D = 1.0  
 E = 1.0

for suitable contents of SPW and SPW1. By further adjusting these constants the multiplication by  $.4056615E-9 \approx 2^{-31}$  could be avoided; but this observation was felt to be beyond the scope of level 4 optimization, although it would occur naturally to any programmer using assembly language.

The most interesting thing here, however, is the effect of subroutine linkage, since the long prologue and epilogue significantly increases the time of the inner loop. The timings for levels 0-3 assume standard OS subroutine conventions, although levels 2 and 3 are able to shorten the prologue and epilogue somewhat because of their knowledge of program flow. For level 4, the subroutine was "opened", placed in the loop without any linkage; hence the sequence of scores,

119.9 , 105.1 , 81.4 , 76.2 , 27.2 .

Without subscripting there is comparatively little difference between levels 0 and 3; this implies that optimization probably has more payoff for FORTRAN than we would find for languages with more flexible data structures.

It would be interesting to know just how many hours each day are spent in prologues and epilogues establishing linkage conventions.

Example 5. The next inner loop is representative of several programs which had to be seen to be believed.

```

DO 1 K = 1,N
M = (J-1)*10+K-1
IF (M.EQ.0) M = 1001
C1 = C1+A1(M)*(B1**(K-1))*(B2**(J-1))
C2 = C2+A2(M)*(B1**(K-1))*(B2**(J-1))
IF ((K-1).EQ.0) T = 0.0
IF ((K-1).GE.1) T = A1(M)*(K-1)*(B1**(K-2))*(B2**(J-1))
C3 = C3+T
IF ((K-1).EQ.0) T = 0.0
IF ((K-1).GE.1) T = A2(M)*(K-1)*(B1**(K-2))*(B2**(J-1))
C4 = C4+T
IF ((J-1).EQ.0) T = 0.0
IF ((J-1).GE.1) T = A1(M)*(B1**(K-1))*(J-1)*(B2**(J-2))
C5 = C5+T
  
```



```

      IF ((J-1).EQ.0) T = 0.0
      IF ((J-1).GE.1) T = A2(M)*(B1**(K-1))*(J-1)*(B2**(J-2))
      CC = CC+T
1    CONTINUE

```

After staring at this for several minutes, our group decided it did not deserve to be optimized. But after two weeks' rest we looked at it again and found interesting applications of "strength reduction", both for the exponentiations and for the conversion of K to real. (The latter applies only in level 4, which knows that K doesn't get too large.) The scores were

1367 , 545 , 159 , 145 , 104 .

Level 1 optimization finds common subexpressions, and level 2 finds the reductions in strength. Level 4 removes nearly all the IF tests and rearranges the code so that C1 and C2 are updated last; thus only  $B1^{**}(K-1)$  is necessary, not both it and  $B1^{**}(K-2)$  .

Example 6. In this case the "inner loop" involves subroutine calls instead of a DO loop:

```

      SUBROUTINE S(A,B,X)          9
      DIMENSION A(2),B(2)         9
      X = 0                        9
      Y = (B(2)-A(2))*12+B(1)-A(1) 9
      IF (Y.LT.0) GO TO 1          9
      X = Y                        5
1    RETURN                        9
      END                          9
      SUBROUTINE W(A,B,C,D,X)      4
      DIMENSION A(2),B(2),C(2),D(2),U(2),V(2) 4
      X = 0                        4
      CALL S(A,D,X)                4
      IF (X.EQ.0) GO TO 3          4
      CALL S(C,B,X)                2
      IF (X.EQ.0) GO TO 3          2
      CALL S(C,A,X)                1
      U(1) = A(1)                  1
      U(2) = A(2)                  1
      IF (X.NE.0) GO TO 1          1
      U(1) = C(1)                  0
      U(2) = C(2)                  0
1    CONTINUE                      1

```

CALL S(B,D,X)	1
V(1) = B(1)	1
V(2) = B(2)	1
IF (X.NE.0) GO TO 2	1
V(1) = D(1)	0
V(2) = D(2)	0
2 CALL S(U,V,X)	1
3 CONTINUE	4
RETURN	4
END	4

The numbers at the right of this code show the approximate relative frequency of occurrence of each statement; calls on this subroutine accounted for 60% of the execution time of the program. The scores for various optimization styles are

1545.5 , 1037.5 , 753.3 , 736.3 , 289 .

Here 270 of the 1545.5 units for level 0 are due to repeated conversions of the constant 0 from integer to real. Levels 2 and 3 move the first statement "X = 0" out of the main loop, performing it only if "Y.LT.0" . The big improvement in level 4 comes from inserting the code for subroutine S in line and making the corresponding simplifications. Statements like  $U(1) = A(1)$  ,  $U(2) = A(2)$  become simply a change in base register.

Perhaps further reductions would be possible if the context of subroutine W were examined, since if we denote  $12*A(1)+A(2)$  by a ,  $12*B(1)+B(2)$  by b , etc., the subroutine computes  $\max(0, \min(b,d)-\max(a,c))$  .

Example 7. In this program virtually all of the time exclusive of input/output editing was spent in the two loops

```

DO 1 I = 1,N
A = X**2+Y**2-2.*X*Y*C(I)
B = SQRT(A)
K = 100.*B+1.5
1 D(I) = S(I)*T(K)
Q = D(1)-D(N)
DO 2 I = 2,M,2
2 Q = Q+4.*D(I)+2.*D(I+1)

```

where array D was not used subsequently. The scores are

744 , 387 , 516 , 292 , 256 .

Here level 1 computes  $X \times X$  by "MER 0,0" instead of a subroutine call, and it computes  $-D \times D(I+1)$  by "AER 0,0" instead of multiplying. Level 4 combines the two DO loops into one and eliminates array D entirely.

(Such savings in storage space were present in quite a few programs we looked at; some matrices could be reduced to vectors, and some vectors could be reduced to scalars, due to the nature of the calculations.

A quantitative estimate of how much space could be saved by such optimization would be interesting.)

Example 8. Ninety percent of the running time of this program was spent in the following subroutine.

```
SUBROUTINE COMPUTE
COMMON ....
COMPLEX Y(10),Z(10)
R = REAL(Y(N))
P = SIN(R)
Q = COS(R)
S = C*6.*(P/3.-Q*Q*P)
T = 1.414214*P*P*Q*C*6.
U = T/2.
V = -2.*C*6.*(P/3.-Q*Q*P/2.)
Z(1) = (0.,-1.)*(S*Y(1)+T*Y(2))
Z(2) = (0.,-1.)*(U*Y(1)+V*Y(2))
RETURN
END
```

This was the only example of complex arithmetic that we observed in our study. The scores

841.5 , 735.5 , 336 , 336 , 249

reflect the fact that levels 0 and 1 make six calls on the complex-multiply subroutine, while levels 2 and 3 expand complex multiplication into a sequence of real operations (with obvious simplifications). Level 4 in this analysis makes free use of the distributive law, e.g.

$S = \cos(P \cdot (1 - \cos(Q)))$ , although this may not be numerically justified.

Furthermore level 4 assumes the existence of a single "SINCOS(R)" subroutine that computes both the sine and cosine of its argument in 1.5 units of time; programmers who calculate the sine of an angle usually want to know its cosine too and vice versa, and it is possible to calculate both in somewhat less time than would be required to compute them individually.

Example 9. A program with 245 executable statements spent 70 percent of its time in

```
DO 2 K = 1,M
DO 2 J = 1,M
X = 0.
Y = 0.
DO 1 I = 1,M
N = (J+J+(I-1)*M2)
B = A(K,I)
X = X+B*Z(N)
1 Y = Y+B*Z(N-1)
DY(L) = W*X
DY(L+1) = -W*Y
2 L = L+2
```

when M was only 5. Scores (for the innermost I loop only) are

84 , 69 , 30 , 24 , 24 ,

reflecting the fact that level 4 cannot do anything for this case.

Example 10. In this excerpt from a contour plot routine, the CALL is only done rarely:

```
DO 1 I = L,M
1 IF (X(I-1,J).LT.Q .AND X(I,J) .GE. Q) CALL S(A1,A2,A3,A4,7,A5)
```

The scores, assuming that  $X(I) \cdot \text{LT} \cdot Q$  about half the time, are

40 , 31.5 , 14.5 , 7.5 , 5 .

Level 3 keeps Q in a register, while level 2 does not. Level 4 is

especially interesting since it avoids testing  $X(I-1,J).LT.Q$  in those cases where it is known to be true from the previous loop. We had noticed similar situations in other routines.

Example 11. This "fast Fourier transform" example shows that inner loops aren't always signalled by the word "DO".

```

1  K = K+1
   A1 = A(K)*C(J)+A1
   B1 = B(K)*C(J)+B1
   K = K+1
   A2 = A(K)*S(J)+A2
   B2 = B(K)*S(J)+B2
   J = J+I
   IF (J.GT.M) J = J-M
   IF (K.LT.M) GO TO 1

```

The scores are

118 , 91 , 60 , 54 , 50 ;

level 4 is able to omit the second "K = K+1", and to use a BXLE for "J = J+I".

Example 12. Unfortunately an inner loop is not always as short as we had hoped. This rather long program (1300 executable statements) spent about half of its time in the following rather horrible loop.

```

DO 3 I = 1,M
JO = J1
IF (JO.EQ.0) JO = J2
J1 = J1+1
J3 = J3+1
J4 = J4+1
IF (J4.EQ.(L(J-1)+1)) J4 = 1
J5 = J1+1
IF (J5.EQ.(J2+1)) J5 = 1
U1 = U(J1,K1,K2)
V1 = V(J1,K1,K2)
W1 = W(J1,K1,K2)
P(J1) = .25*(Q1(I)*(V1+V(J3,K3,K2))*(W1+W(J3,K3,K2))
          +Q2(I)*(V1+V(J3+1,K3,K2))*(W1+W(J3+1,K3,K2))
          -Q3(I)*(V1+V(J4,K4,K2))*(W1+W(J4,K4,K2))
          +D*((U1+U(J5,K1,K2))*(W1+W(J5,K1,K2))
              -(U1+U(JO,K1,K2))*(W1+W(JO,K1,K2))))
          +R1(J1,K1)*R2(K2)*(S(J1,K2+1)*(W1+W(J1,K1,K2+1))
              -S(J1,K2)*(W1+W(J1,K1,K2-1)))

```

```

      IF (I.EQ.1) GO TO 1
      J = J4-1
      IF (J.EQ.0) J = L(J-1)
      P(J1) = P(J1) + .25*Q4(I)*(V1+V(J6,K4,K2))*(W1+W(J6,K4,K2))
      GO TO 2
1     IF (M.EQ.1) GO TO 2
      P(J1) = P(J1) + .25*Q4(I)*(V1+V(J3-1,K3,K2))*(W1+W(J3-1,K3,K2))
      GO TO 2
2     P(J1) = P(J1) + .25*Q4(I)*(V1+V(J2+4,K3,K2))*(W1+W(J2+4,K3,K2))
      CONTINUE

```

Here levels 2 and 3 have just enough registers to maintain all the necessary indices; the scores are

792 , 568 , 242 , 238 , 207 .

Level 4 observes that  $J_6$  can more easily be computed by " $J_6 = J_4$ " before  $J_4$  is changed; and the  $Q_4(I)$  terms are included as if they were conditional expressions within the big formula for  $P(J_1)$  .

Example 13. Here is a standard "binary search" loop.

```

      I = 0
      K = N+1
1     J = (I+K)/2
      IF (J.EQ.I) GO TO 5
      IF (X(J)-X0) 2,4,3
2     I = J
      GO TO 1
3     K = J
      GO TO 1
4     ...
5     ...

```

The scores

$39 \frac{1}{2}$  , 33 , 27 , 21 , 10

for the inner loop are of interest primarily because level 4 was able to beat level 3 by a larger factor than in any other example (except where subroutines were expanded in-line). The coding for level 4 in this case consisted of six packets of eight lines each, one for each permutation of the three registers  $\alpha$  ,  $\beta$  ,  $\gamma$  :

```

L1007  LA  7,0(α,β)
        SRL 7,1
        NR  7,8
        CR  7,α
        BE  L1008
        CE  0,X(7)
        BL  L1008
        BE  L1007
L1008  ...

```

Here  $4I$ ,  $4J$ ,  $4K$  are respectively assumed to be in registers  $\alpha$ ,  $\gamma$ ,  $\beta$ ; register 8 contains  $-1$ . Division by 2 can be reduced to a shift since it is possible to prove that  $I$ ,  $J$ ,  $K$  are nonnegative. Half of the "CR  $\gamma, \alpha$ ; BE L1008" could have been removed if  $X(0)$  were somehow set to  $-\infty$ ; this would save another 10%.

Actually the binary search was not the inner loop in the program we analyzed, although the programmer (one of our group) had originally thought it would be! The frequency counts showed that his program was actually spending most of its time moving entries in the  $X$  table, to keep it in order when new elements were inserted. This was one of many cases we observed where a knowledge of frequency counts immediately suggested vital improvements, by directing the programmer's attention to the real bottlenecks in his program. Changing to a hash-coding scheme made this particular program run about twice as fast.

Examples 14-17. From this point on the programs we looked at began to seem rather repetitious. We worked out four more examples, summarized here with their scores.

```

DO 1 I = 1,N
  C = C/D*R
  R = R+1.
1 D = D-1.

```

[45 , 42 , 27 , 21 , 20]

```

DO 1 J = 1,N
  H(I,J) = H(I,J)+S(I)*S(J)/D1-S(K+I)*S(K+J)/D2
1 H(J,I) = H(I,J)

```

[136 , 103 , 58 , 49 , 41.5]

```

      REAL FUNCTION F(X)
      Y = X*.7071068
      IF (Y.LT.0.0) GO TO 1
      F = 0.5*(1.0+ERF(Y)) } low frequency
      RETURN
1  F = 1.0-0.5*(1.0+ERF(-Y))
      RETURN
      END

```

[219.5 , 208.5 , 191.3 , 191.3 , 151]

```

      DO 1 I = 1,N
1  A = A+B(I)+C(K,I)

```

[41 , 31 , 14 , 9 , 8]

(The latter example is the loop from 015928 to 015A28 in Figure 2.)

Cursory examination of other programs led us to believe that the above seventeen examples are fairly representative of the programs now being written in FORTRAN, and that they indicate the approximate effects achievable with different styles of optimization (on our computer). Only one of the other programs we looked at showed essentially different characteristics, and this one was truly remarkable; it contained over 700 lines of straight calculation (see the excerpts in Figure 3) involving no loops, IF's or GO's ! This must be some sort of record for the length of program text without intervening labeled statements, and we did not believe it could possibly be considered typical.

All but one of the DO loops in the above examples apparently have variable bounds, but in fact the compiler could deduce that the bounds are actually constant in most cases. For instance in Example 17, N is set equal to 805 at the beginning of the program and never changed thereafter.

Table 3 summarizes the score ratios obtained in three examples; 0/1 denotes the ratio of the score for level 0 to the score for level 1, etc.

It may be objected that measurement of the effects of optimization is impossible since programmers tend to change the style of their FORTRAN



U23 = -ES12T*SETN + ES12B*SEBN	264.
U24 = -ES22T*SETN + ES22B*SEBN	265.
U3C = ES66T*SETN + ES66B*SEBN	266.
U3I = -ES66T*SETN + ES66B*SEBN	267.
V3T = -2.*((ES11T+M*ES12T)*SXT+(M*ES22T+ES12T)*SYT)*C2XC2Y	268.
1 -2.*DSQRT(M)*TT*ES66T*S2XS2Y	269.
V3B = -2.*((ES11B+M*ES12B)*SXB+(M*ES22B+ES12B)*SYB)*C2XC2Y	270.
1 -2.*DSQRT(M)*TB*ES66B*S2XS2Y	271.
V4T = -8.*((ES11T+M*ES12T)*SXT+(M*ES22T+ES12T)*SYT)*C4XC4Y	272.
1 -8.*DSQRT(M)*TT*ES66T*S4XS4Y	273.
V4B = -8.*((ES11B+M*ES12B)*SXB+(M*ES22B+ES12B)*SYB)*C4XC4Y	274.
1 -8.*DSQRT(M)*TB*ES66B*S4XS4Y	275.
V5T = -2.*((9.*ES11T+M*ES12T)*SXT+(M*ES22T+9.*ES12T)*SYT)*C2XC6Y	276.
1 -6.*DSQRT(M)*TT*ES66T*S2XS6Y	277.
A(3) = -A11*ML2*2.*X11 - 4.*A22*ML2*4.*X12 - A13*ML2*2.*X11	604.
1 +T1*64.*X13	605.
2 -TML2C*(A11 + 2.*A22 + A13)	606.
3 -4.*FY*SB02*ML2	607.
A(4) = -ML2*(2.*X11*(X12+X13)-BETA*X11/LSC)-A11*Q2S	608.
1 -TML20*(X11/4. +X12 + X13)	609.
2 +(HX*(K11E+M*K12BX)*SA11+M*HY*(M*K22B+K12BY)*SB11	610.
3 +HXY*M*K66H*SC11)/2.	611.
4 +Y3	612.
A(5) = -ML2*X12*16. - A22*C2S*16.	613.
1 -TML20*2.*X13	614.
2 +Y4	615.
B(14,16) = +Y1315	959.
B(14,17) = +Y1316	960.
B(15,14) = B(14,15)	961.
B(16,14) = B(14,16)	962.
B(17,14) = B(14,17)	963.
B(15,1) = 0.	964.
B(15,2) = 0.	965.
B(15,3) = -4.*ML2*FY	966.
B(15,15) = -HY*HY*MSQ*D11B/(2.*DB) + Y1414	967.
B(15,16) = Y1415	968.
B(15,17) = Y1416	969.
B(16,15) = B(15,16)	970.
B(17,15) = B(15,17)	971.
B(16,1) = +ML2*HXY	972.
B(16,2) = 0.	973.
B(16,3) = 0.	974.
B(16,16) = -HXY*HXY*M/(4.*C66B) + Y1515	975.

Figure 3. Excerpts from a remarkable program.

Table 1. Execution speed ratios with various types of optimization.

Example	0/1	0/2	0/3	0/4	1/4	2/4	3/4
1a	1.3	2.7	3.7	5.4	4.1	2.0	1.1
1b	1.0	4.0	4.3	4.8	2.7	1.5	1.1
2	1.2	2.0	4.0	6.6	5.4	2.6	1.4
3	1.2	2.3	6.3	7.4	5.6	3.2	1.1
4	1.1	1.5	1.6	4.4	3.9	3.0	2.8
5	2.5	9.0	9.4	13.1	5.2	1.5	1.4
6	1.5	2.0	2.1	5.4	3.6	2.6	2.5
7	1.0	2.4	2.5	2.9	1.5	1.2	1.1
8	1.1	2.5	2.5	3.4	3.0	1.3	1.3
9	1.0	2.8	3.5	3.5	2.9	1.3	1.0
10	1.3	2.8	5.3	8.0	6.3	2.9	1.5
11	1.3	2.0	2.2	2.4	1.8	1.2	1.1
12	2.2	3.3	3.3	3.8	1.8	1.1	1.1
13	1.2	1.4	1.8	3.9	3.3	2.7	2.1
14	1.1	1.6	2.1	2.3	2.1	1.4	1.1
15	1.3	2.3	2.8	3.3	2.5	1.4	1.1
16	1.1	1.1	1.1	1.5	1.4	1.3	1.3
17	1.3	2.9	4.6	5.1	3.9	1.8	1.1

programs when they know what kind of optimizations are being done for them. However, the programs we examined showed no evidence that the programmers had any idea what the compiler does, except perhaps the knowledge that "1" is or is not converted to "1.0" at compile time when appropriate. Therefore we expect that such feedback effects are very limited.

Note that level 3 and level 4 programs ran 4 or more times as fast as level 0 programs, in about half of the cases. Level 3 was not too far from level 4 except in Examples 4 and 6 where short subroutine code was expanded in line; by incorporating this technique and the idea of replicating short loops, level 3 would come very close indeed to the "ultimate" performance of level 4 optimization. (Before conducting this study, the author had expected a much greater difference between levels 3 and 4 and had been experimenting with some more elaborate schemes for optimization, capable of coming close to the level 4 code in the binary search example above. But the sample programs seem to show that existing optimization techniques are good enough, on our computer at least.)

#### Summary and Conclusions

Compiler writers should be familiar with the nature of programs their compiler will have to handle. Besides constructing "best cases" and "worst cases" it is a good idea to have some conception of "average cases". We hope that the data presented in this paper will help to give a reasonably balanced impression of the programs actually being written today.

Of course every individual program is atypical in some sense, yet our study showed that a small number of basic patterns account for most

of the programs in use. Perhaps these programs can be used to make a more realistic comparison of compiler and machine speeds than is obtained with the "NAME test" [17]. See also F. Bryant's comparison of FORTRAN compilers summarized in [4, Appendix 3, pp. 764-767].

Our sample may not be correct, and so we hope people in other parts of the world will conduct similar experiments in order to see if independent studies yield comparable results.

While gathering these statistics we became convinced that a comparatively simple change to the present method of program preparation can make substantial improvements in the efficiency of computer usage. The program profiles (i.e., collections of frequency counts) which we used in our analyses turned out to be so helpful that we believe profiles should be made available routinely to all programmers by all of the principal software systems.

The "ideal system of the future" will keep profiles associated with source programs, using the frequency counts in virtually all phases of a program's life. During the debugging stage, the profiles can be quite useful, e.g., for selective tracing; statements with zero frequency indicate untested sections of the program. After the program has been debugged it may already have served its purpose, but if it is to be a frequently used program the high counts in its profile often suggest basic improvements that can be made. An optimizing compiler can also make very effective use of the profile, since it often suffices to do time consuming optimization on only one tenth or one twentieth of a program. The profile can also be used effectively in storage management schemes.

In early days of computing, machine time was king, and people worked hard to get extremely efficient programs. Eventually machines got larger and faster, and the payoff for writing fast programs was measured in minutes

or seconds instead of hours. Moreover, in considering the total cost of computing, people began to observe that program development and maintenance costs often overshadowed the actual cost of running the programs. Therefore most of the emphasis in software development has been in making programs easier to write, easier to understand, and easier to change. There is no doubt that this emphasis has reduced total system costs in many installations; but there is also little doubt that the corresponding lack of emphasis on efficient code has resulted in systems which can be greatly improved, and it seems to be time to right the balance. Frequency counts give an important dimension to programs, showing programmers how to make their routines more efficient with comparatively little effort. A recent study [5] showed that this approach led to an eleven-fold increase in a particular compiler's speed. It appears useful to develop interactive systems which tell the programmer the most costly parts of his program, and which give him positive reinforcement for his improvements so that he might actually enjoy making the changes! For most of the examples studied in Section 4 we found that it was possible for a programmer to obtain noticeably better performance by making straightforward modifications to the inner loop of his FORTRAN source language program.

In the above remarks we have implicitly assumed that the design of compilers should be strongly influenced by what programmers want to do. An alternate point of view is that programmers should be strongly influenced by what their compilers do; a compiler writer in his infinite wisdom may in fact know what is really good for the programmer, and would like to steer him towards a proper course. This viewpoint has some merit, although it has often been carried to extremes in which programmers have to work harder and make unnatural constructions just so the compiler writer has an easier job.

When well-timed frequency counts are supplied to a programmer, it will become clear to him just which aspects of a language the implementor has chosen to treat most efficiently: the reporting of this information seems to be the best way to exert a positive influence on the users of a language.

The results of our study suggest several avenues for further research. For example, additional static and dynamic statistics should be gathered which are more meaningful with respect to local optimizations. A more sophisticated study of these statistics would also be desirable.

Our survey seems to have given a reasonably clear picture of FORTRAN as it is now used. Other languages should be studied in a similar way, so that software designers can conceptualize the notion of "typical" programs in COBOL, ALGOL, PL/I, LISP, APL, SNOBOL, etc.

We found that well-done optimization leads to at least a 4- or 5-fold increase in program speed (exclusive of input/output editing) over straight translation, in about half of the programs we analyzed. This figure is based on a computer such as the 360/67 at Stanford, and it may prove to be somewhat different on other configurations; it would be interesting to see how much different the results would be if the seventeen examples were worked out carefully for other types of computers. Furthermore, a study of the performance gain which would be achieved by in-line format editing is definitely called for.

As we discussed the example programs we saw many occasions where it is natural for compiler optimization to be done interactively. The programmer could perhaps be asked in Example 11 whether or not  $J$  will be nonnegative and less than  $2^k$  throughout the loop (so that  $J = J+1$  can be done with a "load address" instruction); in Example 8 he might be asked whether

the distributive law could be used on his formulas; in Example 7 he might be asked if  $X**2+Y**2$  can ever overflow (if not, this calculation may be taken out of the loop); and so on.

As the reader can see, there is considerable work yet to be done on empirical studies of programming, much more than we could achieve in one summer.

#### Acknowledgments

This study would not have been successful without the many hours of volunteer work contributed by members of the group who were not supported by research funds. We also are grateful for computer time contributed by the Stanford Linear Accelerator Center, IBM Corporation, and Lockheed Missiles and Space Corporation.

### Appendix. Examples of hand translation

The following code was produced from

```
DO 2 J = 1,N
  T = ABS(A(I,J))
  IF (T-S) 2,2,1
1  S = T
2  CONTINUE
```

using the various styles of hand translation described in Section 4. Only the inner loop is shown, not the initialization.

#### Level 0.

			<u>Cost</u>
Q1	ST	5,J	2
	L	3,J	2
	M	2,=A(AROWS)	7
	A	3,I	2
	SLL	3,2	2
	LE	0,A(5)	2
	LPER	0,0	1
	STE	0,T	2
	LE	0,T	2
	SE	0,S	3
	BNH	I2	1.5
	B	L1	2 x .5
L1	LE	0,T	2 x .5
	STE	0,S	2 x .5
L2	L	5,J	2
	A	5,=F'1'	2
	C	5,N	2
	BNH	Q1	2

A "dedicated" use of registers, and a straightforward statement-by-statement approach, are typical of level 0.

#### Level 1.

Q1	ST	5,J	2
	LA	3,AROWS	1
	MR	2,5	6
	A	3,I	2
	SLL	3,2	2
	LE	0,A(5)	2
	LPER	0,0	1
	STE	0,T	2



	BNH	L2	2
			1.5
L1	LE	0,0	2 x .5
	PER	0,0	2 x .5
L2	LA	0,1(0,0)	1
	C	0,0	2
	PER	0,1	2

Note the use of LA and LE, the knowledge of register contents, and the removal of the redundant branch. The redundant LE in location L1 is still present because the occurrence of a label potentially destroys the register contents.

#### Level 1.

Q1	LE	0,0(0,0)	2
	LPER	0,0	1
	LER	0,0	1
	SER	0,2	2
	BNH	L2	1.5
L1	LER	0,0	1 x .5
L2	A	0, -A(AROWS*4)	2
	C	0, SPEC	2
	BNH	Q1	2

Here SPEC contains the precomputed address of A(I,N) ; S is maintained in floating register 2.

#### Level 2.

Q1	LE	0,0(0,0)	2
	LPER	0,0	1
	CER	0,2	1
	BNHR	2	1.5
L1	LER	0,0	1 x .5
L2	BYLE	0,0,Q1	2

Here register 2 is preloaded with the address of L2 (for a microscopic improvement), and registers 4 and 5 are preloaded with appropriate values governing the BYLE.

Level 4.

Q1	LE	0,0(0,3)	2 x .5
	LPER	0,0	1 x .5
	CER	0,2	1 x .5
	BNHR	2	1.5 x .5
L1.1	LER	2,0	1 x .25
L2.1	LE	0,4(0,3)	2 x .5
	LPER	0,0	1 x .5
	CER	0,2	1 x .5
	BNHR	6	1.5 x .5
L1.1	LER	2,0	1 x .25
L1.2	BXLE	3,4,Q1	2 x .5

Since the loop program is so short it has been duplicated, saving half of the BXLE's, when proper initialization and termination routines are appended. (The code would have been written

Q1	LE	0,0(0,3)
	LPER	0,0
	CER	0,2
	BHR	2
L2.1	LE	0,4(0,3)
	LPER	0,0
	CER	0,2
	BHR	6
L2.2	BXLE	3,4,Q1
	...	
L1.1	LER	2,0
	B	L2.1
L1.2	LER	2,0
	B	L2.2

if the frequency counts of this program would have given less weight to statement 1.)

Note that the FORTRAN convention of storing arrays by columns would make these loops rather inefficient in a paging environment; a compiler should make appropriate changes to the storage mapping function for arrays in such a case.

## Bibliography

- [1] Allen, R. E. "Program optimization." Ann. Rev. in Automatic Computing 1, 1966, 199-227.
- [2] Allen, R. E. "Compiler performance evaluation: survey and appraisal." Communications of the ACM, 10 (1967), 17-18.
- [3] Allen, R. E. "Measurement of recursive Programs." Ph.D. Thesis, School of Engineering and Applied Science, Univ. of California, Berkeley, California, Report 70-48, May 1970, 100 pp.
- [4] Aho, Alfred and Stewart, Jason E. Programming Languages and their Compilers. Macmillan Institute of Mathematical Science, New York: Macmillan, 1971, 147 pp.
- [5] Barton, Stephen J. and Heller, Steven E. "Streamline your software development." Computer Decisions 2 (October 1970), 39-45.
- [6] Brooks, David H. "Error correction in CORC, the Cornell Computing Language." AFIPS Fall Joint Computer Conference 29 (1974), 15-24.
- [7] Cohen, E. Nathan. "The debugging of computer programs." Ph.D. Thesis, Princeton University, August 1969, 1-3 pp.
- [8] IBM System/360 FORTRAN IV Library: Mathematical and Service Subprograms, File number 11-0-25, Form 228-0513-0, Table 13, Model 1, July 1968, 10 pp.
- [9] Daniels, E. "TIME - A FORTRAN Execution Time Estimator," in preparation.
- [10] Davidson, I. Y. and Johnson, R. H. "Program performance measurement." Stanford Note 45, revision 1, April 1970, Stanford, California, 20 pp.
- [11] Evans, Donald L. "ALGOL-58 - Algebraic Translation on a Limited Computer." Communications of the ACM 12, 11, (November 1969), 18-21.
- [12] Evans, Donald L. Fundamental Algorithms, The Art of Computer Programming, Vol. 1, Reading, Mass.: Addison-Wesley, 1973.
- [13] Fortran, J. G. and Waller, M. E. "FORTRAN - A compiler emphasizing hardware." Communications of the ACM 10, 14-22.
- [14] von Neumann, John and Goldstone, Herman H. "Planning and coding of problems for an electronic computing instrument," 3 vols.; Institute for Advanced Study, Princeton, N. J., 1947-1948; reprinted in von Neumann's Collected Works, Vol. 3, A. H. Taub, ed., London: Hermann, 1963, 33-117.

- [15] Russell, L. C., Jr. "Automatic Program Analysis." Ph.D. Thesis, School of Engineering and Applied Science, Univ. of California, Los Angeles, California, Report 69-13, March 1969, 123 pp.
- [16] Satterthwaite, E. "Source Language Debugging Tools." Ph.D. Thesis, Stanford University, in preparation.
- [17] Schmid, E. "Rechenzeitenvergleich bei Digitalrechnern," Computing 2 (1978), 101-117.
- [18] Wichmann, E. A. "A comparison of ALGOL 68 execution speeds." National Physical Laboratory, Central Computer Unit Report 1, January 1970, 3 pp.
- [19] Wichmann, E. A. "Some statistics from ALGOL programs." National Physical Laboratory, Central Computer Unit Report 11, August 1970, 10 pp.

- [15] Russell, E. C., Jr. "Automatic Program Analysis." Ph.D. Thesis, School of Engineering and Applied Science, Univ. of California, Los Angeles, California, Report 69-12, March 1969, 168 pp.
- [16] Satterthwaite, E. "Source Language Debugging Tools." Ph.D. Thesis, Stanford University, in preparation.
- [17] Schmid, E. "Rechenzeitenvergleich bei Digitalrechnern," Computing 2 (1970), 166-177.
- [18] Wichmann, B. A. "A comparison of ALGOL 60 execution speeds." National Physical Laboratory, Central Computer Unit Report 3, January 1969, 28 pp.
- [19] Wichmann, B. A. "Some statistics from ALGOL programs." National Physical Laboratory, Central Computer Unit Report 11, August 1970, 10 pp.